Simulating large-scale pedestrian movement using CA and event driven model: Methodology and case study

Jun Li, Siyao Fu, Haibo He, Hongfei Jia, Yanzhong Li, Yi Guo

Department of Applied Mathematics, Changchun University of Science and Technology, Changchun, Jilin 130022, China
College of Traffic, Jilin University, Changchun, Jilin 130025, China
Department of Electrical, Computer and Biomedical Engineering, University of Rhode Island, Kingston, RI 02881, USA
College of Mathematics and Statistics, Beihua University, Jilin 132013, China
Department of Electrical and Computer Engineering, Stevens Institute of Technology, Hoboken, NJ 07030, USA

HIGHLIGHTS

- A systematic methodology of using CA and event driven model is proposed.
- The model can reflect behavior characteristics of customers.
- The model can be used to simulate the evacuation of pedestrian flows in indoor areas.
- The model can be used to investigate the layout of shopping mall.

ABSTRACT

Large-scale regional evacuation is an important part of national security emergency response plan. Large commercial shopping area, as the typical service system, its emergency evacuation is one of the hot research topics. A systematic methodology based on Cellular Automata with the Dynamic Floor Field and event driven model has been proposed, and the methodology has been examined within context of a case study involving the evacuation within a commercial shopping mall. Pedestrians walking is based on Cellular Automata and event driven model. In this paper, the event driven model is adopted to simulate the pedestrian movement patterns, the simulation process is divided into normal situation and emergency evacuation. The model is composed of four layers: environment layer, customer layer, clerk layer and trajectory layer. For the simulation of movement route of pedestrians, the model takes into account purchase intention of customers and density of pedestrians. Based on evacuation model of Cellular Automata with Dynamic Floor Field and event driven model, we can reflect behavior characteristics of customers and clerks at the situations of normal and emergency evacuation. The distribution of individual evacuation time as a function of initial positions and the dynamics of the evacuation process is studied. Our results indicate that the evacuation model using the combination of Cellular Automata with Dynamic Floor Field and event driven scheduling can be used to simulate the evacuation of pedestrian flows in indoor areas with complicated surroundings and to investigate the layout of shopping mall.

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1. Introduction

Emergency evacuation problem of large shopping mall has attracted increasing attention among researchers. However, it is challenging because pedestrian evacuation is very difficult to be observed, and a real-life experiment for evacuation is almost impossible. The early research started from using static methodologies. This is often done as a preliminary analysis and due to the lack of computational resources. These methods have limitations attributed to the fact that the evacuation process is dynamic with chaos and instability, rather than static, which make such models unsuitable to model the details and complexity of evacuation scenarios.

In order to study the dynamic evacuation processes, later research has been focused on using macroscopic model to research pedestrian crowd behavior features [1]. Which, though similar to the gas-kinetics or fluid-dynamics, they are impractical for real-application since the numerical solution of fluid-dynamic system equations are typically hard to obtain. What is worse, such kinds of model ignore individual characteristics. Therefore, a promising research direction is to consider the individual pedestrian movement model instead, by using microscopic model representing individuals as basic units of the system [2]. There are a few application cases available, such as social force model [3,4], Cellular Automata [5] and intelligent agent [6]. However, to the best of our knowledge, there is no report on the combination of Cellular Automata and event driven model.

Being proposed by Von Neumann and Ulam in 1960s, CA (Cellular Automata) has been employed to explore the implicit biological self-reproduction of biological systems [7–9]. Compared with other models, CA is an extremely efficient model for computer simulation, which makes it suitable for a series of disciplinary crossing societies, ecology, physics, chemistry, traffic science, environmental science, general computer science, and so on. CA also has a widespread application in pedestrian flow modeling and pedestrian evacuation [10–28].

Event driven model and agent based model are the major approaches in simulation modeling [29]. Event driven model is based on the concept of entities and resources. Compared to event driven model, agent based model pay more attention on agent rather than systematic characteristic. The global behavior emerges as a result of many individuals. Wagoum et al. [30] proposed an event driven way finding in a graph-based structure for pedestrians in an evacuation scenario. The operational level of the pedestrian walking is described by the Generalized Centrifugal Force Model, which operates in continuous space. Chraibi et al. [31] simulate pedestrian dynamics based on the event driven method and the social force model. They defined an event as a single occurrence of a change in the forces acting on a pedestrian. Campanella et al. [32] presented a hybrid pedestrian management algorithm based on optimized time-based simulation and an event-driven simulation.

Motivated by the aforementioned research achievement, this paper proposes a CA based approach for modeling human dynamic mobility in a large-scale commercial shopping mall. The overall goal of this exploratory study is to investigate the potential of CA methods for simulating human mobility behavior under normal shopping situation and evacuation caused by emergency events that threaten the safety of the public. In order to do this, both human mobility behavior and its surrounding dynamics need to be embedded into overall framework. To this end, our system consists of two parts: Cellular Automata with Dynamic Floor Field and event driven scheduling. A four-level scheme was proposed for the overall simulation model, and pedestrian movement are modeled by Dynamic Floor Field, local constrained motion rules, as well as general motion behavior. A large-scale commercial shopping mall has been developed for testing and validating the effectiveness of simulation models on both normal and emergency evacuation scenarios. The simulation results clearly reveal the different mobility behavior characteristics of pedestrian flows under normal shopping scenario and emergency case. We also provide the detailed analysis of the overall evacuation accumulation time and the number of pedestrians, as well as exits’ width. Our model could be useful for optimize layout design of large-scale commercial shopping mall.

The rest of this work is organized as follows: the related works are discussed in detail in Section 2. Section 3 describes our proposed model, including the overall framework, simulation scenario, system events, model representation and dynamic pedestrian behavior. The Dynamic Floor Field model formulation is presented in Section 4, which also gives out the pedestrian’s local motion rules. Section 5 shows our simulation results, which includes the algorithm flowchart, normal movement behavior, emergency evacuation scenario, the distribution of customer shopping time, customer traffic, evacuation time accumulation and its relationship with exit’s information. Section 6 concludes our work.

2. Related work

Different modeling methods based on Cellular Automata have been used to develop simulations for studying human behavior during evacuation. Numerous situations have been investigated, such as evacuation with obstacles [10–14], evacuation from fires [1,15], evacuation in poor visibility [16,17], evacuation in panic situation, evacuation from aircraft [18], etc.

Usually, there are obstacles in the evacuation scenario inside buildings. The interaction among and between pedestrians and obstacles during evacuation process should be analyzed. Some researchers studied modeling and simulation of evacuation with obstacles. Varas et al. [10] proposed a bi-dimensional CA model to simulate the process of evacuation of pedestrian in a room with fixed obstacles. A Floor Field is defined in the paper, and a panic parameter is also introduced. Eng Aik et al. [11] proposed a modified dynamic CA model to simulate the evacuation of occupants from a room with obstacles. The model takes into account human emotions and crowd density around the exits, but did not consider the density of other places. Liu et al. [12] proposed a modified CA evacuation model to simulate an evacuation experiment conducted in a classroom with obstacles. They considered the impact of the occupant density around exits on human behavior in
evacuation. Zhang et al. [13] studied the pedestrian evacuation problem in stadium with or without obstacles using CA model. A multi-agent individual decision-making framework is given, in which the action direction of each pedestrian (called agent) is determined by the distance of the agent to the exits, the number and density of agents and obstacles within the view field of the agent. All pedestrians in the stadium have been divided into four classes: young male, young female, old male and old female. In evacuation process, the weighting that affects individual decision-making between each class of agents is different. Alizadeh [14] proposed a dynamic CA model to simulate the evacuation process in the rooms with obstacles. Besides the basic parameters such as human psychology, placement of the doors, doors' width, positions of the obstacles and light of the environment, distribution of the crowd plays an important role in this model.

The combination of CA and other methods, such as social force model, game-theoretic approach, is also a common method. The game-theoretic approach is an essential tool in the research of conflicts of pedestrian behaviors. A conflict game and a CA model are combined to research on strategy of evacuees and evacuation time [19]. Fang et al. [20] studied the evacuation process in a teaching building with two neighboring exits. The exit–selecting phenomenon in the experiment is analyzed. Song et al. [21] proposed a multi-grid model with force essentials, i.e. repulsion, friction and attraction, to study the evacuation behaviors at exit, and compared its performance with the social force model. A force-driving CA model is proposed to investigate the evacuation behaviors of pedestrians at a T-shaped intersection [22]. Tissera et al. [1] presented a hybrid model where the dynamics of fire and smoke propagation are modeled by means of CA and people behavior are simulated by goal oriented intelligent agents. According to the characteristics of passengers in a terminal of airport, M. Schultz et al. [18] presented a discrete microscopic simulation model for passenger motion behavior, the model is based on an enhanced CA model, and it considers repulsion potentials, friction effects, and path finding algorithms. CA has already been extensively applied in the research of the high-rise building evacuation problems. The pedestrian movement process of high-rise building evacuation can be divided into three stages: moving toward an exit on each floor, staircase evacuation and refuge floor transition [23]. The game-theoretic approach can be used to research crowd dynamic conflicts during evacuation processes. Conflict game and CA model are combined to research on frequency of strategy and evacuation time of each evacuees [19].

As for pedestrian flow modeling, some studies use Floor Field to simulate pedestrian movement [15,24–27]. Zheng et al. [15] investigate the process of pedestrian evacuation under the influence of the fire situation. They introduced an extended fire Floor Field. A CA model is presented to simulate the evacuation process in a closed square with partition wall. The model defines a Floor Field and takes into account exit–selection and social forces [24]. Direction visual field is used to represent the prediction on the tendency of pedestrian flow [25]. By considering the direction visual field, a modified Floor Field is used to simulate the pedestrian evacuation behavior in a room with multiple exits. Huang et al. [26] proposed a modified Floor Field model to simulate pedestrian in room with internal obstacles and multiple exits. They also give a new calculate method of Floor Field. Tanimoto et al. [27] proposed an improved CA model, which both Static Floor Field and collision effect based on game theory were considered. This model proved that outflow rate from an evacuation exit can be improved by placing an appropriate obstacle in front of the exit.

In addition to the use of CA on pedestrian evacuation simulation model, the following models are also included: lattice gas models [28,33,34], social force models [3,35], fluid-dynamic models [36,37], agent-based models [6,38], game theoretic models [39], and approaches based on experiments with animals. Zheng et al. [40] identified seven methodological approaches for crowd evacuation in building. Zheng et al. also pointed out that psychological factor and physiological factor should be considered when we research individual and collective behavior in evacuation.

3. Simulation model

As mentioned previously, the commercial shopping area design will be crucial for public safety. In this section, we consider methodology for modeling pedestrian movement by event driven scheduling model.

3.1. General simulation methodology overview

Fig. 1 shows the simulation framework of our methodology.

3.2. Simulation scenario

To better address the evacuation methodology presented in Section 3.1, we design a square-shaped commercial shopping mall for simulation. Fig. 2 shows the simulation environment, which is a 80 m × 80 m grid partitioned by 200 cells × 200 cells. The walls take 1 cell and shelves range from 1 to 3 cells according to different type of stores. There are 61 different stores in total in our simulation setting. To make the model more accustomed to real–world scenario, we assume that during the normal shopping period, customers will move by following their specific Floor Fields. Also, the density of crowd area and various pedestrian weaving situations have been taken into consideration particularly. We would like to point out that this is the most complex single floor environment ever used in such research community, compared with existing researches.

Generally, the simulation experiment considers two cases: normal situation and emergency situation. In normal situation, the system operates in normal status, which means both the customers and the clerks will follow their regular daily activities: customers go shopping by following their individual purchasing requirement and perform specific path planning...
strategy; while clerks are responsible for interaction with customers. When emergency happens (such as fire alarm or other issues threatens the safety of public), the shopping mall will announce the status via broadcasting and start evacuation process, in which both customers and clerks follow the evacuation model defined in our model, which will be discussed in the next section.

3.3. Discrete event simulation

Typically, events are scheduled dynamically as the simulation process, following the general daily shopping schedule defined in our system. Generally speaking, there are 6 categories of system events in the overall scheduling task. The detailed descriptions of these six categories are given as follows:

1. Entering shopping mall event.

The entering interval among customers can be described by following Poisson distribution, Exponential distribution, or Erlang distribution. For the simplicity of computation, in this work we use Poisson distribution to model the event of customer entering shopping mall (notice that the simulation clock is calculated by walking per cell) as follows:

\[ P(X = k) = \frac{e^{-\lambda} \lambda^k}{k!} \]  \hspace{1cm} (1)
where \( X \) is a discrete random variable representing population enters into the mall area. \( \lambda \) stands for the accumulation for arrival of customers during certain amount of time, which reflects the variance of customer traffic during different times of a day. Once a customer has been modeled by Eq. (1), the corresponding purchase intention (where or which store the customer wishes to go for shopping) will be saved as vector (purchase intention vector), by doing so it is possible to model the arrival of customers in different stores to follow certain types of distribution. Therefore, any customer will be assumed to move along the Floor Field generated by first destination store, the corresponding system events would be triggered once a customer enters the store. It is important to note that normally a customer will leave from the door he entered intuitively. However, during the emergency, a customer will try his best to find the nearest exit to evacuate.

2. Entering store event.

Assume that the service time follows the exponential distribution with parameter \( \tau \):\
\[
f(t) = \begin{cases} \tau e^{-\tau t}, & t > 0 \\ 0, & t \leq 0 \end{cases}
\] (2)

Obviously, the expectation of the \( f(t) \) is \( 1/\tau \), which indicates the average staying time of one customer. Consequently, it is reasonable to generate the corresponding time one customer stays inside the store. In such conditions, a customer generally performs a random move pattern. Once the accumulating time meets the activation requirements of finishing shopping event, the customer leaves the store and moves along his next shopping destination.

3. Leaving store event.

This event will be triggered by the time of entering store event. Customer switches from the previous Floor Field to another one generated by next moving destination, and he navigates himself along the new Floor Field till destination arrives.

4. Lunch time event.

In most large-scale commercial shopping mall there will be a food court serving food for customers (and clerks/shop assistants as well), especially during lunch time (around 11:00 am–1:00 pm). During this time, customers will face the option of whether going to take lunch meal, keep shopping, or leave. We model this event by Poisson distribution and the length of customer’s mealtime follows Erlang distribution with parameter \( \mu \):
\[
f(t) = \begin{cases} \frac{\mu^k t^{k-1} e^{-\mu t}}{(k-1)!}, & t \geq 0, \mu \geq 0 \\ 0, & \text{others} \end{cases}
\] (3)

where \( \mu \) represents rate parameter, and \( k \) is the shape parameter. Similar to stores, since food court is also some grids, therefore, the option of whether waiting in a line for meal or directly going to the seat will depend on the availability of seats, which can be implemented via queuing approach.

5. Clerk’s operation event.

In normal situation, similar to customers, clerks will prefer to stay in the stores dealing with interaction with customers. They typically will follow the regular random movement pattern.

6. Emergency evacuation event.

The activation of emergency evacuation event states that the overall system enters into “normal–emergency-broadcasting–evacuation” pattern. During this stage, all the status of customers and clerks will be modified as evacuation pattern. They will discard all the movement patterns generated by the current Floor Field and begin to follow the global Floor Field formulated by exits. Reasonably, they will find the nearest exit for a fast evacuation.

3.4. CA model representation

As mentioned previously in the literature review, the pedestrian mobility behavior modeling in a shopping mall is challenging due to its spatial–temporal complexity. Generally speaking, modern shopping center’s inner locations are usually spatially-distributed with a complex geometric form. Apart from that, during customer–shop interaction, shopping demand varies differently among different categories of customers (age, gender, etc.). In particular, each customer has his/her unique shopping preference in terms of time and place. On the other hand, shop assistants normally stay inside the shop and thus their motion behavior are distinct from those of customers. It would be drawn from aforementioned aspects that the pedestrian mobility behavior modeling is a complex spatial–temporal function regarding both specific shopping location and transportation location. Consequently, the Floor Field of these spatially-discriminative places should be taken into consideration. We proposed in this paper a multi-layer CA model. The key idea is to represent the shopping model via quadruples: System = \{Environment, Customer, Clerk, Trajectory\}.

Correspondingly, each component has a functional layer, thus, Environment layer, Customer layer, Clerk layer and Trajectory layer, all of which are synchronized by environment layer. Compared with traditional CA model, our multiple-layer model is more flexible and extendible. The functions of these layers are briefed as follows:

1. Environment layer.

Environment layer, i.e. cellular layer, indicates the occupancy situation of each cell. The values of cell \( cell_{ij} \) are given as follows:
\[
cell_{ij} = \begin{cases} 1, & \text{if } (i, j) \text{ is occupied} \\ 0, & \text{otherwise}. \end{cases}
\] (4)
Fig. 3. Relationships of stores, customers, and clerks.

Note that all the cells form matrix Cell, in environment layer, cell is represented as a square grid (0.4 × 0.4 m²). All cells that cannot be occupied have been marked as black (for instance, customer and clerk cannot enter the cell that belongs to wall or shelf). Generally, environment layer considers information including exit position, store’s position, store’s parameters (clerk number, customer number, customer’s average staying time, and Static Floor Field, etc.).

All store’s information will be stored in Environment layer, as shown in Fig. 3.

2. Customer layer.

All customer’s information will be stored in Customer layer, as shown in Fig. 3.

As mentioned, a customer enters the shopping mall via entry following the time interval given by Poisson distribution. The purchase intention vector is generated when a customer enters, and so with the corresponding motion path plan. Whether a customer enters one specific store or not depends on the saturation level of this store. The patterns of human walks and Lévy walks contain some statistical similarity. Random way point (RWP) or Brownian motion (BM) cannot model human mobility. Brockmann et al. [41] show Lévy walk patterns in human travels over the scale of a few thousands of kilometers using bank note travel patterns. Gonzalez et al. [42] use tracking information of 100 000 mobile phone users to show that human walks have heavy-tail flight distributions. Rhee et al. [43] study the mobility patterns of humans up to the scales of meters and seconds, and they argue that the mobility of people contains similar statistical features to those found in Lévy walks. Lévy random walk can give a more realistic representative statistics about the pedestrians’ dynamics. Therefore, once entered in, the customer will move inside the store by Lévy random walking strategy [43,44]. Note that each customer only occupies one cell, and can only move into those cells that are not occupied by other customers and clerks.

3. Clerk layer.

All clerk’s information will be stored in Clerk layer, as shown in Fig. 3.

Fig. 3 illustrates the relationship among stores, customers, clerks, and scenarios. In an effort to model customer’s mobility among different stores, or between store and shopping center exit, we build store’s Floor Field using currentOrigin and currentDestination parameters, which regulates the motion behavior of one customer following specific store’s Floor Field. In other words, the value of customers(i).currentDestination should quote the value of Scenario.positionOfExit or the index of a store. Similarly, the value of customers(i).currentOrigin should quote the index of a store. The purpose of these quotes is to compute the Floor Field. The customer’s staying time follows Eq. (2) in terms of timeAtStore. Stores(j).timeAtStore is the mean time of all customers shopping in stores(j), and random variable customers(i).timeAtStore has a distribution (Eq. (2)). A specific customer has his/her own value of timeAtStore which should obey this distribution. As a comparison, one clerk’s currentOrigin and currentDestination parameters regulate his motion behavior under regulation of floor field of the store with which he/she works. The value of clerks(k).currentDestination should quote the value of Scenario.positionOfExit or the index of a store. Similarly, the value of clerks(k).currentOrigin should quote the index of a store.

Similar to customers, clerks will move inside the store by Lévy random walking strategy. Each clerk only occupies one cell, and can only move into those cells that are not occupied by other clerks and customers.

4. Trajectory layer.

As an independent layer which does not affect the whole system, trajectory layer only record trajectories of customers and clerks.

3.5. Movement pattern

The movement patterns of pedestrians include regular normal mobility behavior and emergency mobility behavior. Empirical study of pedestrian flow can be traced back to the year 1937. There are many papers that focus on fundamental diagram, which proposed the pedestrian’s velocity–density relationship of facilities, such as stairs, ramps, bottlenecks,
halls, etc. Empirically, the average velocity of a pedestrian is about 1.3 m/s. In our simulation setting, the size of a cell is 0.4 m $\times$ 0.4 m. The setting of speed can be adjusted by finer discretization of space. In other words, a pedestrian occupies several cells, and the speed can be set with different values [45–48]. For traditional CA model, a pedestrian occupies one cell, and the speed is usually set as integer times of the width of the cell. This setting is appropriate to modeling of large-scale scenario. Take into consideration of the scenario of shopping mall, we adopt the traditional CA. We suppose the walking speed of pedestrian during normal situation is 1.2 m/s (3 cells) in open area, while they will slow down to 0.4 m/s (1 cell) inside store. The time step of system clock is set to 1/3 s under normal condition, i.e. the time of a pedestrian moving one cell in the corridor. That is to say a pedestrian inside store can move a cell each 3 time steps, but a pedestrian in open area can move a cell each time step. A pedestrian has faster velocity under emergency. We set pedestrians velocity as 2.4 m/s during emergency evacuation, so the time step is 1/6 s under emergency.

1. Customer’s movement pattern.

Normally customer’s movement pattern is decided by system’s status. If the system is in normal situation, then customer will move from store to store (or exit) by following the motion path generated by purchase intention and Floor Field. Customer’s moving behavior inside store will be regulated by Lévy random walking [43,44]. On the other hand, in situation of emergency, then all customers will move toward exit following the path generated by Floor Field of exit. The information of the customer in system will be deleted as soon as he moves out of the exit.

2. Clerk’s movement pattern.

Similar to customer, if the system is in normal situation, then clerk will move inside store by Lévy random walking [43,44]. Clerks generally will stay inside the store unless they go to food court during lunch time. On the other hand, in situation of emergency, then all clerks will move toward exit following the path generated by Floor Field of exit. The information of the clerk in system will be deleted as soon as he moves out of the exit.

To model pedestrian flow in a shopping mall is a complicated process. The shopping mall usually has complex geometrical structure, while each customer’s trajectory tends to several stores because of his purchase intention. Each customer has personalized start time and end time. The trajectories of clerks are different with the trajectories of customers because clerks are walking mostly in particular stores. All these factors lead to a complicated pedestrian flow in a shopping mall. Although both customer and clerk follow Lévy random walking rule, their walking characteristics are spatio-temporally different. In particular, customer follows Lévy random walking in shop units listed on purchase intention and exit sequences, which is simulated by a point of long-distance walk among stores, short-distance walking inside stores, and long-distance walk among stores once again. On the other hand, clerks only do Lévy random walking inside the store.

4. Formation of Floor Field

Floor Field is proposed by Burstedde et al. [49], and Floor Field is subject to diffusion and decay. Furthermore, it can be modified by the motion of the pedestrians. The model calculates the Static and Dynamic Floor Field, corresponding to the influences of geometry and pedestrian movement. Generally, Static Floor Field is applied for calculating the distance between shopping mall’s entry/exit and any stores inside the shopping mall, while Dynamic Floor Field focus more on the density of crowdedness and its influence on the field. The concept of Floor Field has been used in many evacuation models.

4.1. Static Floor Field

Without loss of generality, suppose that Floor Field formed by stores and Floor Field formed by exits of shopping mall are generated by same program but with different parameters.

In the process of computing Static Floor Field, $f_{ij}$ indicates minimum steps which a pedestrian moving from $(i, j)$ to destination only walking in horizontal and vertical directions. $e_{ij}$ indicates minimum steps which a pedestrian moving from $(i, j)$ to destination walking in horizontal, vertical and diagonal directions [26,49]. $d_{ij}$ is weighted sum of $f_{ij}$ and $e_{ij}$. $S_{ij}$ indicates the value of Static Floor Field at position $(i, j)$ formed by destination. The weighted parameter $\varepsilon$ in Eq. (7) has influence on the shape of the crowd near an exit. In fact, while $\varepsilon = 1$, i.e., pedestrian only walking in horizontal and vertical directions, then Static Floor Field will form a triangle near the destination, and while $\varepsilon = 0$, i.e., pedestrian walking in horizontal, vertical and diagonal directions, then Static Floor Field will form a rectangle near the destination. The value of parameter $\varepsilon$ must reflect the characteristics of pedestrian flow, and one of these characteristics is arching near exit. According to the area discussed in this paper, when $\varepsilon = 0.4$, the shape of the crowd is approximately an arching. Computing procedure of Static Floor Field is shown in Fig. 4 [26]. Fig. 5 shows an illustration of Static Floor Field generated by an exit, in which a high value means pedestrian is closer to the exit, and vice versa. As can be seen from the figure, the potential is very heavy around the exit, forming arching and this reflects the typical characteristics of the crowd gathered at the exit. Normally, a pedestrian will move forward to the exit following the Dynamic Floor Field which is generated by both Static Floor Field and the density of pedestrians. Therefore, the Dynamic Floor Field varies from time to time during the simulation. The computing method of Dynamic Floor Field will be described in Section 4.2.

Fig. 6 shows the Static Floor Field generated by a store ($\geq 50$). Similar to the Floor Field generated by exit, a pedestrian (customer) will move forward to the store following the Dynamic Floor Field which is generated by both Static Floor Field and the density of pedestrians. As can be seen from the figure, the Static Floor Field generated by store $\geq 50$ is not symmetrical, in which a high value means pedestrian is closer to the store $\geq 50$, and vice versa.
4.2. Dynamic Floor Field

For the consideration of crowd avoidance, a customer will try to avoid any densely populated area, which is highly dynamic. However, there are places in which high density are inevitable, such as corridor corner or exit. Only use Static Floor Field will encounter the problem of "deadend", meaning that pedestrians moving in opposite directions will stuck into the same cell, even though there are other cells available nearby. To this end, we try to make pedestrians move to low density area by taking the local density information into account. Specifically, we compute the Dynamic Floor Field by using following equations considering both density of pedestrians and the Static Floor Field value.

\[
\text{density}_{ij} = \sum_{i'=i-1}^{i+1} \sum_{j'=j-1}^{j+1} \text{cell}_{i'j'}
\]

\[
dynamic_{ij} = \text{static}_{ij} \times \left( 1 - \alpha \cdot \frac{\text{density}_{ij}}{9} \right).
\]

Eq. (8) computes the density of cell, while Eq. (9) stands for the Dynamic Floor Field value, where cell is a binary value (0 for available, 1 for occupied). density stands for the density value of cell, which value range is \(\{k | k = 0, 1, 2, \ldots, 9\}\). dynamic means the Dynamic Floor Field value of cell, \(\alpha\) is the control parameter responsible for adjusting the density field in terms of density. Eq. (9) means linearly decreasing the value of the Static Floor Field, in which \(\alpha\) is the penalty factor sensitive to the density of population in the area. For one cell, it is expected that after penalization, Dynamic Floor Field of
densely populated area shall be lower than that of loosely populated area. It is easy to infer that once a cell has been occupied by pedestrians, it will not be overlapped by other entries even if the cell lies in low density area. In addition, we do not need to compute Dynamic Floor Field for walls and shelves, because we set as a special value in order to forbid pedestrians to enter these cells.

It should be noted that in our density computing model, we only consider the cells which are next to each other, as shown in Fig. 7(a). But it is perfectly fine to comfortably extending the range to the neighbor region within 2 cells. Fig. 7 compares the visualization of Static Floor Field, density of pedestrians, and Dynamic Floor Field generated in same local area in our simulation environment. The numbers in Fig. 7(b) indicate the density of the pedestrian of each position. A circled number also indicates that position was occupied by a pedestrian. As can be seen from Fig. 7(a) and (c), the variation of the Floor Field reveals the fact that Dynamic Floor Field has been significantly suppressed near these cells occupied by pedestrians, which means that followed by our proposed dynamic model, customers will actively avoid to approach densely populated area. \( \alpha \) is empirically set as 0.1 in our experiment. As can be seen from Fig. 8, the distribution of the values of Dynamic Floor Field is not smooth when \( \alpha \) is larger than 0.2. Meanwhile, the penalty of density is not enough when \( \alpha \) is too small (e.g. \( \alpha \) is equal to 0.02). The reasonable value range is [0.05, 0.2] in our experiment. Although it is noteworthy that different Static Floor Field may lead to different values of \( \alpha \).
4.3. Local motion rule

We used Moore motion rule in our proposed CA model, other motion rules, such as Von Neumann, or Margolus, can be applied as well, yielding similar performances. The Moore motion rule and its transition probability are shown in Figs. 9 and 10, respectively.

Transition probability of a pedestrian move into cell \( i_j \) is computed as follows:

\[
P_{ij} = Z \cdot \exp(\beta \cdot \text{dynamic}_{ij}) \left( 1 - \mu_{ij} \right) \xi_{ij}
\]
where parameter $Z$ represents normalization factor.

$$Z = \left( \sum_{i,j} \exp(\beta \cdot \text{dynamic}_{ij}) (1 - \mu_{ij})\xi_{ij} \right)^{-1}$$  \hspace{1cm} (11)

$$\mu_{ij} = \begin{cases} 0, & \text{if } (i,j) \text{ is vacant} \\ 1, & \text{if } (i,j) \text{ is occupied} \end{cases}$$  \hspace{1cm} (12)

$$\xi_{ij} = \begin{cases} 0, & \text{if } (i,j) \text{ is wall or shelf} \\ 1, & \text{otherwise} \end{cases}$$  \hspace{1cm} (13)

where parameter $\beta$ is the reflection of the pedestrian’s familiar with intrinsic features of scenarios. When $\beta$ increases, time of pedestrian movement will generally decrease, which means the more familiar a customer gets with the environment, the faster he will move around.

5. Simulation results

In this section, we will illustrate and analyze the simulation results.

5.1. Flowchart of simulation algorithm

In accordance with Fig. 1, Fig. 11 shows the flowchart of evacuation simulation algorithm based on CA and event driven scheduling.

5.2. Shopping scenario

The scenario that customers shopping according to their purchase intention under normal status is shown in Fig. 12. We generate the customer population flow using Eq. (1) following Poisson distribution. Without loss of generality, the $\lambda$ varies different time range, such as lunchtime, dinnertime, or afternoon, etc. Each customer is generated by accompanying his purchase intention vector, which determines the customer’s shopping motion behavior inside the shopping center. Once the customer enters into one store, the staying time will be estimated by Eq. (2) following exponential distribution. In particular, lunch intention follows Poisson distribution and lunch time follows Erlang distribution. Customers and clerks move according to Dynamic Floor Field generated by their respective destinations, and the movement pattern is described in Section 3.5. Following the initial assumption of our model, customer’s motion behavior in purchase intention list and exit
sequence priority selection follows Lévy random walk. Consequently, it is straightforward to imagine that a customer will walk relatively long distance before he enters into a specific store in which he walks in short and irregular manner. The pattern repeats when a customer leaves store and goes to the next one till the shopping intention vector has been traversed and algorithm terminates.

5.3. Customer traffic

As mentioned before, the customer arrival time has been modeled using Poisson distribution in Eq. (1), which reflects the variation of customer shopping strategy during various time. For example, it is generally believed that the shopping rush hour arrives its peak during a weekday’s afternoon or early evening, while during a weekend, shopping peak arrives early than usual (around 10:00 am–3:00 pm). Accordingly, in our simulation system, total customer traffic throughout the day is 7035 on a weekday and 12160 during a weekend, while the peak statistics are 355 and 683, respectively.

5.4. Distribution of customers’ shopping time

Fig. 13 shows the customer dynamics on a weekday. The mean of the customer staying time is 19.28 min and standard deviation is 4.15 min. Fig. 14 shows the same dynamics on Saturday, while the statistics changed to 61.18 min and 11.91 min correspondingly. It is apparent to see that during a weekday, customers generally will not stay long in a shopping mall, which
indicates that they tend to have specific and short shopping list in mind. While customers generally will spend more time lingering in a shopping mall and do large shopping during a weekend.
5.5. Emergency evacuation

When emergency happens, all the status of pedestrians (customers and clerks) will be changed as evacuation pattern. They will discard their current movement patterns and begin to follow the Dynamic Floor Field generated by exit. Different scenarios of evacuation are shown in Fig. 15. In emergency situation, evacuation speed is 2.4 m/s (6 cells). Fig. 15(a) describes what happens at the beginning of emergence evacuation, in which pedestrians walk out of stores and move toward exit. Temporary strand and congestion avoidance could be observed in the intersection. Also, when emergency evacuation event triggers, pedestrians tend to move to exit by following the shortest distance rule which, in reality, depends on the pedestrian’s familiarity of the scenario. In our simulation, we assume that emergency evacuation is clearly notified inside the shopping center in an effort to facilitate fast evacuation. Fig. 15(b) presents a pedestrian’s behavior by following the instruction. Thus, the majority of them have arrived to the main evacuation exits shown in both sides, resulting a highly populated pedestrian flow. Such a flow will dissipate gradually as shown in Fig. 15(c) and Fig. 15(d) shows the ending stage. Once again, it has to be pointed out that during emergency evacuation scenario, there is no difference between customers and shop clerks in terms of mobility behavior, since their ultimate goals are exact the same: to get out of the shopping mall as soon as possible.

5.6. Relationship between emergency evacuation time and width of exit

Fig. 16 shows the implicit relationship between emergency evacuation time and width of exit when customer traffic reaches its saturation level (1000). Available Safe Evacuation Time (ASET) means the duration time from the beginning of emergency to the endure limit, which is sensitive to a bunch of factors (such as emergent event type, scenario spatial characteristics, among others), and the time setting varies accordingly. We assume that the ASET in our simulation is 360 s, all pedestrians should evacuate from shopping mall within this time period for safety. It can be seen from the figure that clogging will appear if the width is small (less than 6 cells, see Fig. 17 for further details), which indicates the longer evacuation time. Our empirical experiment results on even larger shopping mall map show that wider exit will not guarantee that all the pedestrians could be evacuated in a short time, since there could be some customers who are far away from exit.
and it takes longer time for them to reach the exit. As a result, more emergency exits should be activated for the sake of efficient evacuation.

In addition, for large shopping malls, business operators often use annular store layout structure, in order to extend customers’ stay time and increase the probability of customers to buy. However, considering the evacuation route choice and to shorten the evacuation time, adopting more exits and checkerboard structure design is an ideal choice.

5.7. Relationship between evacuation time and number of pedestrians

Research indicated that pedestrians in a shopping area will show the characteristic of small group [2]. Following Poisson distribution, customers generally form various sizes of groups in different stores. The peer-to-peer distance among pedestrians will, in general, decrease following the increasing density of pedestrians, which should be viewed as a factor affecting the total evacuation time. In view of this, we present the following simulation results considering different customer density in Fig. 17. As can be seen from the figure, the total evacuation time has an approximate linear relationship when width of exit is larger (bigger than 8). However, it shows a rapid increase when exit width shrinks to 6.

From analysis in Sections 5.6 and 5.7, we can see that the width of exit should not be less than 6. For safety purposes, a wider exit or other exits should be considered.

5.8. Scenario of multi-exits

As described in Sections 5.6 and 5.7, if there is only one exit in a large shopping mall, some pedestrians cannot be evacuated in time because they are far away from the exit. Moreover, it can easily cause pedestrians’ panic when pedestrians flock to the exit. Multi-exits is a proper solution if the surrounding of shopping mall permits. Figs. 18 and 19 show the Static Floor Fields with two exits and four exits respectively. Obviously, the number and the layout of stores have to be readjusted in order to set more exits for safety.

By setting multi-exits, the evacuation time is greatly reduced. Fig. 20 shows the relationship between evacuation time and number of pedestrians under three different layouts of exits, i.e., single exit, two exits and four exits which are shown in Fig. 5, Figs. 18 and 19, respectively. As can be seen in Fig. 20, compared with a single exit situation, evacuation time is reduced by nearly half when two exits are adopted, and evacuation time is reduced to nearly a quarter when four exits are adopted. Moreover, another point that can be observed is, the width of exit has less effect when multi-exits can be adopted.
Fig. 18. Static Floor Field generated by two exits.

Fig. 19. Static Floor Field generated by four exits.

Fig. 20. Relationship between evacuation time and number of pedestrians under different layouts of exits.
6. Conclusions

The evacuation process in a shopping mall has attracted considerable attention in transportation science. In this present study, we proposed a model based on Cellular Automata with Dynamic Floor Field and event driven scheduling, which simulates pedestrian movement in normal situation and emergency situation. The simulation adopts the idea of simulation of service system. There is a function to generate customers in a random way. Purchase intention of a customer is generated based on a function when the customer is coming. Clerks are considered walking randomly in stores before emergency happens. Pedestrians (customers and clerks) are considered walking based on Cellular Automata rules and Dynamic Floor Field. Probability of walking is computed based on Dynamic Floor Field. Floor Field value of a cell will be decreased if some pedestrians are around it, in order to other pedestrians enter it with lower probability (actually to avoid jamming).

A large-scale commercial shopping mall has been developed for testing and validating the effectiveness of the proposed simulation model. The relationship between the evacuation time and the exit width has been analyzed, clogging phenomenon can be observed if the width is too small. As the number of pedestrians increased, the total evacuation time gets longer, especially when the exit width is too small. Further experimental results on larger mall map and scenarios of multi-exits show that more emergency exits should be designed for safety. The simulations and experiments indicate that the evacuation model using the combination of Cellular Automata and event driven scheduling can be used to simulate evacuation process in indoor area and to investigate the layout of building in the design phase. However, more studies should be performed to further research the mechanism of evacuation under emergency situation to make the shopping mall evacuation much safer and more effective.

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References

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